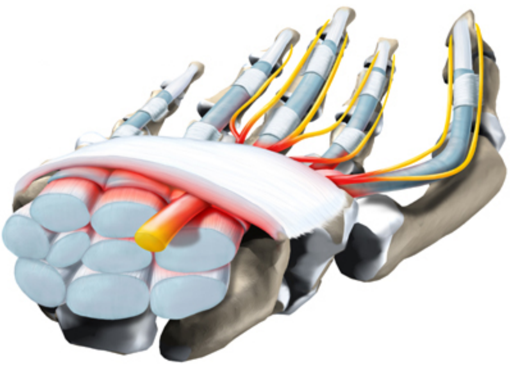
Graduation internship

Thesis

Carpal tunnel syndrome: Reliability of automatic border detection of median nerve in ultrasonography



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Abstract

Carpal tunnel syndrome (CTS) is the most commonly diagnosed peripheral neuropathy due to entrapment. This syndrome is currently being diagnosed clinically, often confirmed through the use of neural conductivity studies (NCS). Over 25 percent of the cases are still missed using this method, while NCS also cause discomfort to the patient. This is why other methods of diagnosis are being sought after, among which ultrasonographic imagery.

It is thought the enlargement of the median nerve at the level of the carpal tunnel plays a role in the development of CTS. To further investigate this claim, the characteristics of the median nerve at this level are being investigated.

A former study has been conducted to establish average values of these characteristics. For this study transversal cine loops of the proximal side of the carpal tunnel have been obtained from a population of 50 patients with CTS and 23 controls. Using software developed by the Erasmus Medical Center, the median nerve has been evaluated by manually placing tracing points around its perimeter. This method yielded the perimeter, cross-sectional area and circularity of the median nerve. Manual tracing however proves to be very time consuming and incorporates elevated levels of inter- and intra-rater variability.

The assignment for this graduation internship was to develop an algorithm to automatically determine the parameters mentioned above. Furthermore the reliability of this method had to be compared to the manual tracing method.

The algorithm developed in this internship makes use of automated border detection, also known as minimal cost analysis or dynamic programming.

To facilitate the process of development and testing, a database has been developed to store the results in a hierarchy of patients and trials.

The area, perimeter and circularity found by the algorithm were evaluated on its differences compared to the manual tracing method. Furthermore the amount of overlap between the areas found by the algorithm and the manual tracing method was assessed. The areas found by the algorithm approximately overlap the manual tracing data by 80%. Furthermore a trend is perceived where smaller shapes are overestimated, while larger contours are underestimated.

Based on these findings, a number of improvements have been suggested. First of all the average size of the median nerve should be taken into account when trying to find the nerve's contour in order to make a better estimate. The algorithm is applied iteratively, as to use the findings of earlier iterations as an approximation of the shape to be found. By adding an additional iteration, the algorithm's findings would come even closer to the actual shape. Finally, by evaluating mean intensity gradients instead of local intensity gradients, noise is removed. This would improve the outcome of the algorithm.

Acknowledgement

This internship could not have taken place without the terrific people at the Erasmus Medical Center. They created an environment in which I feel I really could reach my full potential. The amount of responsibility that was given to me, the high level of expertise of those involved and the pleasant way of communicating resulted in a great collaboration.

First I would like to thank Hans Bosch, associate professor at the department of *Biomedical Engineering*. He coached me throughout the entire development of the software and has the remarkable ability to explain complex concepts in a very clear and pleasant manner. His thorough knowledge on the subject of edge detection in ultrasonography proved invaluable for the outcome of the project.

Another person that cannot remain unmentioned is Ruud Selles, assistant professor and group leader of the *Hand Surgery and Rehabilitation* research group. He played an important role in defining the expectations of this project, by combining his ideas with the advice of others. His extensive track record in clinical research was of great value when defining the test procedure for the algorithm.

Last but not least I would like to thank Anika Filius, PhD student at *Hand Surgery and Rehabilitation*. She taught me everything I needed to know on the subject of carpal tunnel syndrome, both through theory and practice. Her guidance during my literature study on the subject was a great help. She offered me a great opportunity to experience the subject in real life, by involving me in her current research and allowing me to help her make ultrasonographic recordings of patients who suffer from carpal tunnel syndrome.

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Chapter 1

Introduction

This report discusses a graduation internship which took place at the research group of *Hand Surgery and Rehabilitation* at the *Erasmus Medical Center* in Rotterdam, the Netherlands. During this internship an algorithm has been developed to assess the cross-sectional area, perimeter and circularity of the median nerve in ultrasonographic imagery. Furthermore its reliability has been evaluated compared to the method currently used involving manual tracing the perimeter of the nerve.

1.1 Background

The most commonly diagnosed peripheral neuropathy[1] due to entrapment is carpal tunnel syndrome (CTS)[3]. The cause is a narrowing in the carpal tunnel, resulting in compression of the median nerve. This causes numbness and pain in the thumb, index and middle finger, as well as a part of the ring finger. In more severe cases of CTS, the ball of the thumb is also affected, ultimately evolving into decay of its muscles.

CTS is currently diagnosed clinically, often confirmed through the use of neural conductivity studies (NCS). Studies report an elevated variability in both sensitivity[2] and specificity[3] of NCS, resulting in around 25 percent of all the CTS cases being missed[2]. Moreover, NCS causes discomfort for the patient.

Other methods of diagnosis are sought-after to tackle these shortcomings. A plausible candidate is ultrasonography, which has the advantage of being painless and cheaper in regard to NCS while showing promising results in terms of improved sensibility and specificity[4]. Ultrasonographic diagnosis of CTS is done by evaluating the median nerve in the transversal plane at the proximal side of the carpal tunnel. Its area, circularity, perimeter and movement at this level are factors which can indicate the presence of CTS.

The research group of *Hand Surgery and Rehabilitation* at the *Erasmus Medical Center* in Rotterdam is currently evaluating ultrasonography as a diagnostic tool for CTS. The above mentioned factors are determined through the use of a program written in MATLAB, by manually placing tracing points around the perimeter of the median nerve. Based on this information, the program then returns the requested values.

This process however proves to be very time consuming. Moreover, studies show an elevated

[1] Damage to nerves outside of the brain and spinal cord
[2] A measure of the proportion of actual positives which are correctly identified as such
[3] A measure of the proportion of actual negatives which are correctly identified as such

inter[4]- and intra-rater[5] variability when using manual tracing compared to automatic methods to determine characteristics of the heart[1]. It is to be expected that this phenomenon can also be perceived in the area of CTS diagnosis.

This algorithm is the next step in a series of developments to establish ultrasonography as a diagnostical tool for CTS. It is suspected that an enlarged median nerve can be a sign for CTS. To prove this hypothesis, a study was conducted on a population of 50 patients with CTS and 23 controls. Ultrasonographic cine loops[6] were taken from the proximal[7] side of the carpal tunnel in the transversal plane and evaluated using the manual tracing method mentioned above.

1.2 Assignment

The assignment of this graduation internship was to develop an algorithm to automatically determine the median nerve's cross-sectional area, perimeter and circularity in ultrasonographic imagery. Furthermore the reliability of this method had to be compared to the manual tracing method.

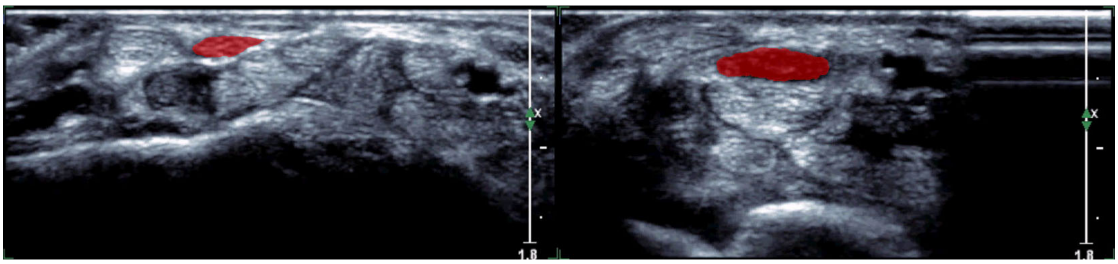


Figure 1.1: Transversal ultrasonographic image of proximal side of carpal tunnel with highlighted median nerve of a healthy person (left) and a CTS patient (right)

1.3 Company

This graduation internship was part of a collaboration between the research group of *Hand Surgery and Rehabilitation* and the *Biomedical Engineering* research department of the thorax-center of the *Erasmus Medical Center* in Rotterdam, the Netherlands. A short introduction on both these parties, with their history and focus points, is given below.

1.3.1 Hand Surgery and Rehabilitation

The research group of *Hand Surgery and Rehabilitation* is an initiative from two departments, namely the department of *Rehabilitation Medicine and Physical Therapy* and the department of *Plastic and Reconstructive Surgery.* It was established in 2006 in order to combine the extensive experience from these departments in both research and clinical care. This effort resulted in a research group in which members from a broad range of disciplines could collaborate to tackle a large number of subjects related to hand surgery and rehabilitation. These subjects are divided

[4]inter-rater variability is the degree of variation among raters
[5]intra-rater variability is the degree of variation among multiple repetitions performed by a single rater
[6]Sequence of images
[7]The side facing the arm

into three themes, namely the development and evaluation of new interventions for patients with hand disorders, as well as assessment tools for hand functions and improving the understanding of underlying mechanisms of diseases and interventions.

These themes cover a large patient group, which in turn is also divided into more specific patient groups which suffer from hand trauma, congenital hand deformities, pain disorders, chronic disorders or disabilities resulting from strokes.

The research group collaborates with a number of departments within the *Erasmus Medical Center*, but also with a number of both national and international research groups.

It is this research group who formulated the graduation internship assignment.

1.3.2 Biomedical Engineering

The *Biomedical Engineering* research group of the *Thoraxcenter*, a partnership between the *Cardiology* and *Cardiothoracic Surgery* department, focuses on technical research regarding the origin, diagnosis and treatment of cardiovascular diseases. Its main interests are ultrasound imaging and vascular biomechanics. The research on ultrasound imaging entails all physical and technical aspects of ultrasound for cardiac diagnosis, like medical ultrasound transducers, ultrasound contrast agents, 2D and 3D imaging methods, and ultrasound image processing. This internship is greatly dependent on this knowledge and will build on the rich development history of this group.

Chapter 2

Project organization

As stated before, this graduation internship builds on research previously done in both CTS diagnosis and area determination in ultrasonography. As a result, the project organization was well defined.

2.1 Problem owner

The problem owner for this assignment was Ruud W. Selles, PhD, assistant professor and group leader of the *Hand Surgery and Rehabilitation* research group. He supervises the work of post-doctoral researchers and students doing research for their PhD, Master's or Bachelor's degree.

2.2 Consulting experts

The consulting expert on the subject of carpal tunnel syndrome was Anika Filius, MD. She is a PhD student at *Hand Surgery and Rehabilitation*, and did research on the reliability of manual measurements in ultrasonography of the median nerve and flexor tendons.

Johan G. Bosch, PhD, was the consulting expert on image processing of ultrasonographic imagery. As an associate professor at the department of *Biomedical Engineering*, he specializes in 2D and 3D ultrasonographic image processing and analysis, as well as transducer development. His research focuses on optimal border detection approaches, geometrical and statistical models, and anatomical and physical knowledge representations for border detection.

2.3 Software development

The internship consisted of developing the algorithm and assessing its reliability. The concepts on which the algorithm functions were established in close collaboration with Johan G. Bosch, while the test procedure was developed with Ruud W. Selles.

Chapter 3

Functional design

This chapter will focus on the concepts on which the functionality of the algorithm is based. The way the image is interpreted is discussed, as well as the method to calculate the perimeter of the median nerve accordingly.

3.1 Interpretation pyramid

Images, among which ultrasonographic cine loops, can be interpreted in a number of ways. The interpretation pyramid is a method to sort these ways according to complexity and is shown in figure 3.1 on page 15 [1]. Interpretation on the lowest level of the pyramid for example only consider individual pixel values without taking into account its surroundings. One level up uses this information to finds patterns like intensity gradients in an image. The next step evaluates this gradients to determine edges and regions.

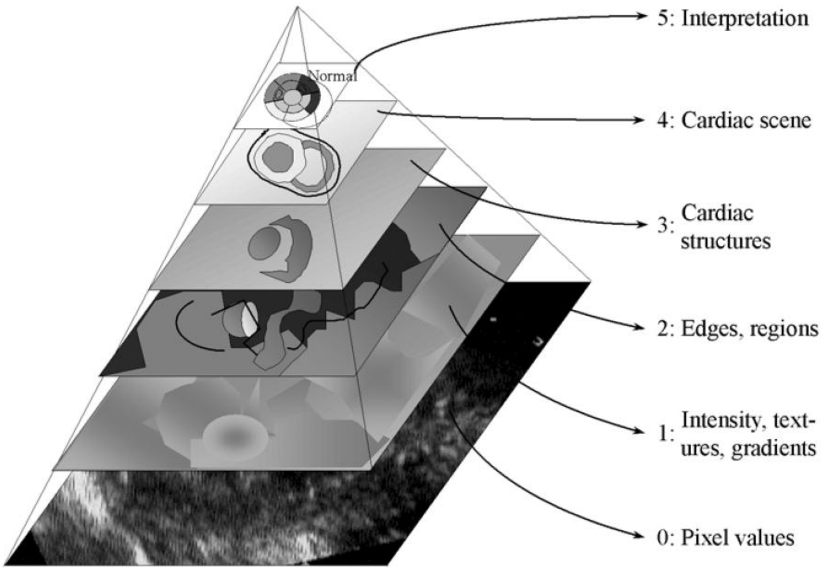


Figure 3.1: Interpretation pyramid

In the levels mentioned above, no knowledge on the actual object itself is required to evaluate the image. These methods can be used on any image, be it a picture of a flower or an ultrasonographic image of the carpal tunnel. The highest levels however do incorporate information about the object in the image. Information about tissue structures is used, for example assumptions about the average shape and size of the median nerve, as well as the scene in which these structures reside, like the carpal tunnel and its tendons. The highest level of the pyramid reflects the way human beings interpret images. It makes use of all the information mentioned above, as well as a profound insight on the exceptions and variations within an image.

The algorithm works on the level of tissue structures. It finds the edge of the median nerve by evaluating intensity gradients in an image while taking into account the nerve's shape. That is, since the nerve has a smooth surface, the perimeter found by the algorithm is not allowed to be jagged.

3.2 Minimal cost analysis

The median nerve is a blob-like structure with an average cross-sectional area of 10 mm^2. Its shape approximates an oval, smooth shape. In ultrasonographic imagery, it is generally darker than its surrounding tissue. However, when there's adjacent fluid, the median nerve is brighter than the fluid.

The image appearance is quite noisy due to ultrasound speckle and the median nerve cannot be characterized by grey value only, so it is not possible to find the median nerve by simple thresholding. The position of the edge of the median nerve is mostly characterized by a strong gradient (dark to light when going from inside to outside). However, due to the noisy image characteristics, strong gradients are present throughout the image. Therefore, a robust edge-based border detection is needed, which is guided by a shape approximation. A well-known technique from echocardiography that uses similar assumptions is dynamic programming, or minimal cost analysis[1].

In conclusion, the algorithm evaluates intensity gradients to find the edge of the median nerve. It does not however take into account its position within the scene of the carpal tunnel. A user has to indicate the approximate center of the median nerve in order for the algorithm to work. The steps to find the nerve's perimeter are illustrated in figure 3.2 on page 18.

The image is only evaluated in an circular shaped area around the center. To determine the median nerve's edge in this area, the image is resampled along scan lines perpendicular to the shape's perimeter. The resulting sample lines are stacked onto one another to create a two-dimensional image in which the nerve's perimeter can be perceived as a path.

This is where the actual functionality of the algorithm comes into play. Its functionality is based upon the principle of dynamic programming, also known as minimal cost analysis or the traveling salesman problem. The latter is a well-known mathematical problem about a salesman who has to visit a number of interconnected cities while traveling the least amount of distance and visiting each city only once.

A minimal cost analysis is used to find a path with the overall lowest cost. The implementation of the algorithm is such that instead of finding the path with the lowest cost, it finds the path with the highest cost, i.e. it actually makes use of a maximal cost analysis.

To translate the problem of edge detection of the median nerve into a maximal cost analysis, intensity gradients have to be viewed as costs. Areas with little difference in intensity are cheap, while high intensity gradients yield high rewards. The goal is to find the overall connective path with the highest cost, while traveling from the bottom to the top of the image. Moreover, since the median nerve has a smooth surface, restrictions are imposed in the amount of deviation allowed per step upwards. If these restrictions would not be imposed, the algorithm would come up with the most expensive path which could have any shape, thus ignoring the information about the median nerve's shape. The principle of restrictions is shown in figure 3.2 on page 17.

Given these restrictions, the analogy to the traveling salesman problem becomes apparent. Choosing the shortest distance from city to city in general does not yield the shortest overall route as the following example demonstrates. Say there are four interconnected cities as shown in figure 3.2 on page 17. Starting from city A, the shortest route leads to B. From here, this tactic leads to D. However, since A has already been visited, the only possibility is the very costly travel to C. To travel the least amount of distance, the order should be A, C, B and D.

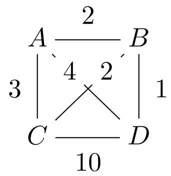


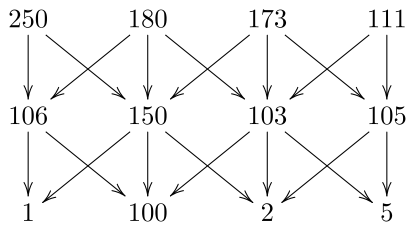
Figure 3.2: Traveling salesman problem

The same rhetoric goes for finding the path with the lowest cost to find the median nerve's perimeter. By following the path with the highest intensity gradients, or lowest cost, in the beginning of the journey to the top of the image, the path might end up in an area with very low intensity gradients, or high costs. This is why it is important to evaluate the entire image when choosing a path, by looking at cumulative costs instead of individual costs of an area.

To calculate the cumulative cost of a position, the cost of that position has to be augmented with the highest cumulative cost of the row below within the given restrictions. Doing so results in a position with the highest cost on the top of the image, from which the ideal path can be found by backtracking, each time choosing the position with the highest cumulative cost. This method yields the path with the overall highest reward in the image.

100	30	23	6
6	50	3	100
1	100	2	5

(a) Cost matrix



(b) Cumulative cost matrix with restrictions

Since the path represents a perimeter, it needs to be closed, i.e. have roughly the same starting and ending point. Since the top and the bottom of the median nerve can often better be perceived than the sides, it was decided to start the resampling of the image from the bottom of the shape, as to take advantage of the high intensity gradient at this position. Starting from the top was disqualified since this position is often close to the border of the ultrasonographic image, which has a very high intensity gradient, resulting in a possible faulty starting point.

The found path is then projected onto the original image. Due to the restrictions mentioned above this path might not reflect the actual shape of the median nerve accurately enough. That is why this sequence, or iteration, of resampling, path finding and projecting is repeated. This time, the image is resampled based on the contour found in the previous iteration, providing a better estimate of the actual shape.

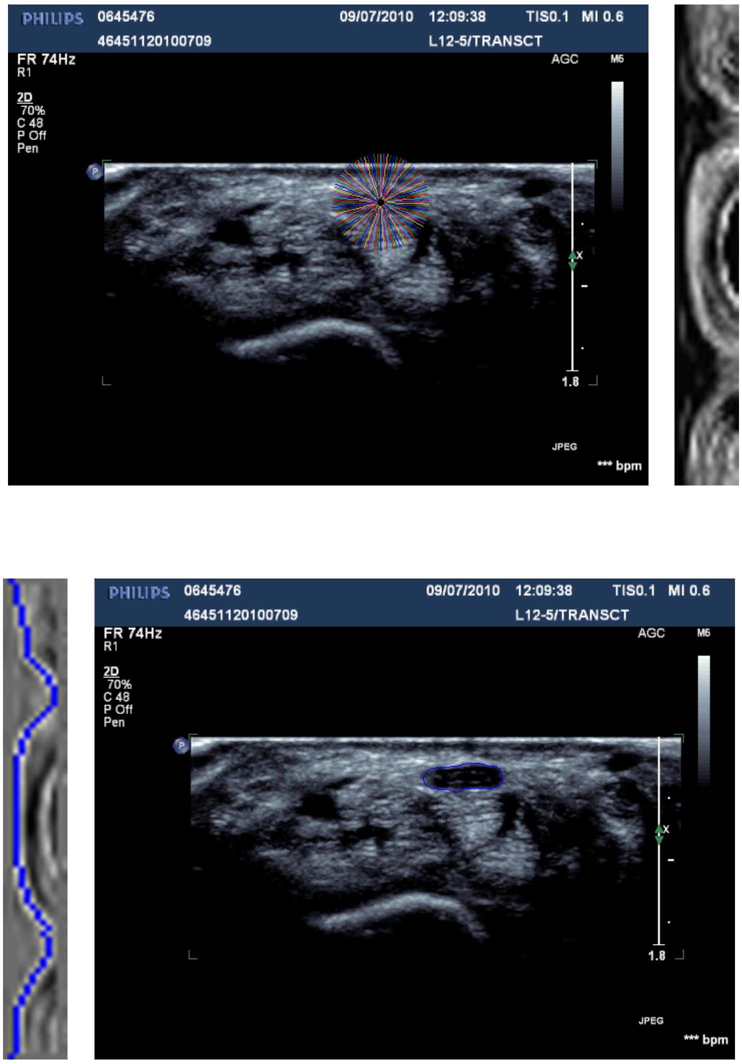


Figure 3.3: Demonstration of algorithm

3.3 Test driven design

By first determining how the algorithm would be tested, the data used to evaluate the algorithm could be established. This way the software development could be geared towards producing and comparing these values.

The goal of this study was to determine the reliability of the algorithm compared to the manual tracing method. As such the same population was evaluated with both methods. This population consisted of 50 CTS patients and 26 controls. In clinical research it is customary to divide the population in a training and a test set. The training set is used to develop the method, i.e. the algorithm, and the test set is used to evaluate its outcome. It was chosen to only evaluate the training set for this thesis as to save the test set for a scientific publication.

Furthermore, to assess information about the intra rater variability, every cine loop was to be evaluated a number of times by the same rater. This way it could be determined how much the outcome differs based on the slight variations in the coordinates given as an approximation of the median nerve's center.

Three values were used to assess the reliability of the algorithm compared to the manual tracing method, being the perimeter, circularity and cross-sectional area of the median nerve. The difference of the area, perimeter and circularity found by the algorithm is mapped to the data obtained through the manual tracing method. Furthermore, the cross-sectional areas were evaluated on the amount of overlap, as to compare both the size and the location of the found area.

Chapter 4

System design

This chapter will discuss the implementation of the algorithm. The software development consisted of two parts, namely the algorithm and a database. The database was used to facilitate the test procedure, storing both the manual tracing data and the data obtained through the use of the algorithm. This way the reliability of the algorithm could conveniently be compared to the manual tracing method.

4.1 MATLAB

The algorithm is developed with MATLAB. Most of the software development at the Erasmus Medical Center is done in this language, resulting in a valuable source of expertise. Since the manual tracing method also made use of software developed in MATLAB, its data are stored in MATLAB files. By choosing this language, these data were easily attainable.

4.2 Database

A database was designed and developed in which the data mentioned above could be stored. Its structure is shown in figure 4.1 on page 22. This design is object oriented and as such is implemented with MATLAB classes. These classes bear much resemblance to C++ classes. Four classes were defined in total, which will be discussed below in greater detail. By using an object oriented approach, entities could easily be upgraded without affecting the rest of the database.

4.2.1 Data structure

The class describing instances highest in the hierarchy of the data structure is the trialClass, meaning that all the data are ultimately stored in an instance of the trialClass. The trialClass contains the trial amount to determine the intra rater variability as well as a time stamp of the moment of storage. Furthermore, it is an aggregation of controls and patients, which both inherit from the patientClass.

For every control or patient in a trial, an instance of the patientClass is initiated. It contains a patientID, the set of which the patient or control is a part of, i.e. the training or test set, and a cineLoopID corresponding to the cineloop which has been evaluated. This last variable is needed since there are several cine loops per patient.

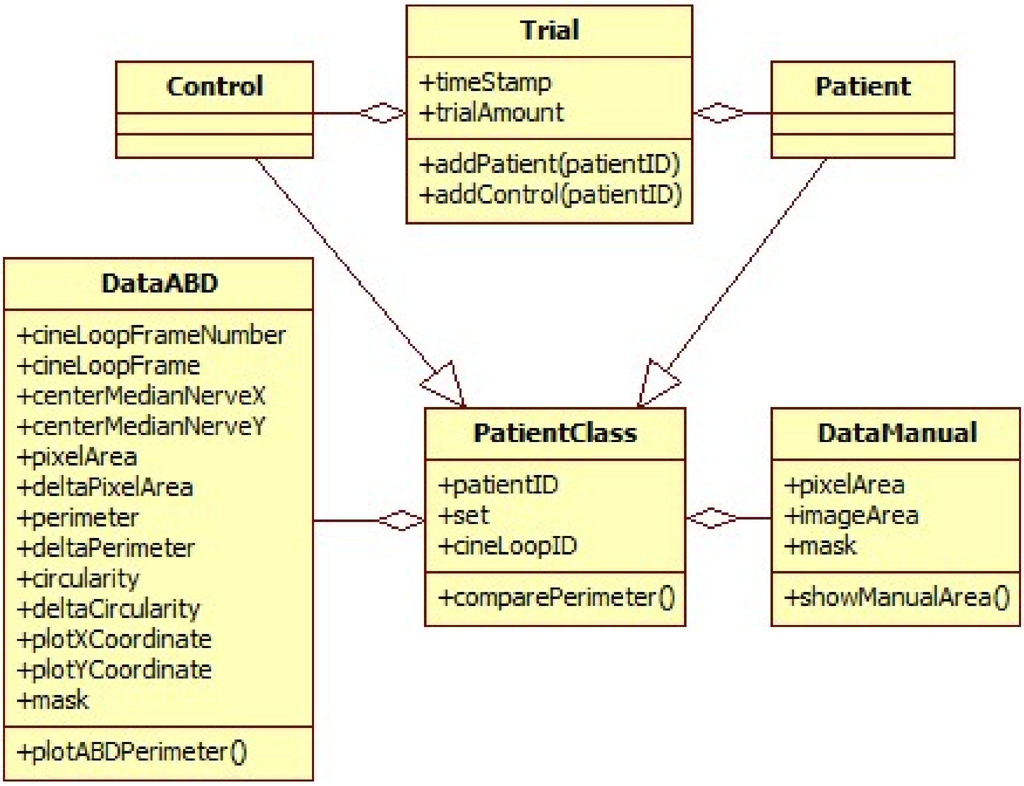


Figure 4.1: Data structure

The manual data and data from the algorithm, respectively stored in a dataManualClass or dataABDClass, are aggregatively connected to the patientClass.

The dataManualClass simply stores the perimeter's size, the rate of circularity and the cross-sectional area of the median nerve obtained through the manual tracing method. The cross-sectional area is stored by means of a two-dimensional matrix in which a mask is stored with the size and location of the area. This way the amount of overlap between the area found by both methods can easily be determined.

The data mentioned above obtained through the use of the algorithm are stored in an instance of the dataABDClass. Furthermore, data used by the algorithm itself are also stored, being the evaluated frame and corresponding number of the cine loop, as well as the coordinates of the median nerve's center as given by the user. Finally the results from the algorithm and its reliability test are stored as the coordinates of the contour and the difference of the area, perimeter and circularity compared to the manual tracing method.

4.2.2 Filling the database

Before the database could be used to store results from the algorithm, first all the manual tracing data, cine loop frames and coordinates of the median nerve's center had to be added. Since the manual tracing data was stored in MATLAB files, all the relevant data could simply be copied to the appropriate location in the database. The cine loop frames used by the algorithm were selected based on the manual tracing data, making sure the same frames were evaluated by both methods. Finally the coordinates of the median nerve were assessed by showing all the selected frames sequentially five times in a row, yielding five sets of coordinates for the median nerve per cine loop, making it possible to determine the intra rater variability.

4.3 Algorithm

The algorithm uses a sequence of steps mentioned earlier, of which the implementation will be discussed below. Every step is contained within a function.

4.3.1 Generating scan lines

The cine loop frame is resampled along scan lines perpendicular to a given shape. As discussed earlier, in the first iteration a circular shape is used to base the resampling upon. The second iteration uses the shape found in the first to resample the image. Scan lines have a couple of parameters which have an influence on the resulting resampled image, being the amount of scan lines, the starting point and direction, the number of samples taken per scan line and the space between these samples.

The starting point of the scan line and its direction are determined by the given shape. The starting point is simply the set of coordinates of the shape at a given location, while a range around the starting point is taken to establish the tangent of the shape at this position. The scan line's direction can be deducted from this information, since it stands perpendicularly to the tangent.

4.3.2 Resampling the image

Based on the scan lines generated in the previous step, the image is resampled using cubic interpolation. This way samples taken along a scan line are put in a two-dimensional matrix, in which each row represents a scan line. This results in an image of the unfolded median nerve on the left, and its surroundings on the right.

4.3.3 Determining the path

In order to determine the path, the resampled image first has to be evaluated on its intensity gradients. To determine this gradient, the average intensity of an area left and right from this point is determined. The median nerve in general has a lower intensity than its surroundings, which can be perceived as a dark area at the left of the resampled image. As such, intensity gradients from low to high when evaluating a sample line from left to right are sought after. This is done by subtracting the intensity value of the left area from the right area mentioned above, as to yield a high outcome in cases where the area on the left is darker than the area on the right.

The next step is to create a two dimensional matrix containing cumulative costs based on the intensity gradients found. To find the value of a position in this matrix, the intensity gradient at that point has to be augmented with the highest value in the row below within a certain range of positions.

As with the parameters of the scan lines, this range also varies throughout the iterations. Since little can be said about the actual shape of the nerve in an early stage, a higher amount of differentiation is allowed, i.e. a larger range of position is allowed. As the algorithm moves through the iterations the range is decreased, allowing less differentiation between scan lines. This philosophy is based on the fact that if the found path exactly matches the perimeter of the median nerve, the perimeter can be perceived as a straight line in the resampled image, thus needing no differentiation left or right.

The highest row in this matrix contains the highest value of the matrix, which is the starting point of the path. Within the same restrictions as mentioned above, the path is constructed by choosing the highest value per row, while moving down the matrix.

4.3.4 Transforming the path

To serve as a shape for following iterations, the path has to be transformed into a connective perimeter. This is done by viewing the position of the path as a section of the scan line. Since the starting point and direction of the scan line is known, the coordinates of the path can be determined.

4.3.5 Smoothing the path

To ensure the path is connective and to remove small deviations, the path is smoothened. The path is copied and pasted one after another, to create a path three times the size of the original path. This lengthened path is smoothed, after which the middle section is extracted. This way the original path length is obtained, while having a guaranteed connective path.

4.3.6 Testing the reliability

The determination of the reliability of the algorithm compared to the manual tracing method is based on three parameters, being the area, perimeter and circularity. To assess the variability in outcome based on the coordinates of the approximate median nerve's center as given by the user, each cine loop frame has been evaluated five times. This resulted in five sets of coordinates per cine loop frame which were used to test the algorithm.

The entire population consists of 50 patients with CTS and 26 controls, which were divided in a training set and a test set. The cine loops were evaluated on the quality of the recording. In order for the algorithm to yield sensible results, the image had to be zoomed in on the area of the carpal tunnel. This would ensure the frame rate of the recording to be around 70Hz. Some recordings were not zoomed in, causing the frame rate to drop which resulted in motion blur. Motion blur causes the edges to be badly perceivable, making it hard for the algorithm to determine the contour of the median nerve. Blurred cine loops were considered to be faulty recordings and were thus excluded from the reliability test.

The circularity and the perimeter found by the algorithm were evaluated on their difference to the manual tracing data.

The area is evaluated on its amount of overlap by using the dice's coefficient, which ranges from 0 (no overlap) to 1 (complete overlap). This coefficient is determined with the following formula, where X and Y respectively represent the area found by the algorithm and by the manual tracing method:

$$\frac{2|X \cap Y|}{|X| + |Y|}$$

Chapter 5

Results

This chapter will focus on the results from the reliability test of the algorithm. To avoid clutter in the graphs used to show the results, the mean from the five results per cine loop frame is shown.

5.1 Area

The reliability of the area found by the algorithm can be seen in figure 5.1 on page 25, where the dice coefficient is mapped to manual tracing data in pixels. Each dot represents the mean of the result from the five sets of coordinates.The mean dice coefficient of the entire population is 0.80, with a standard deviation of 0.12.

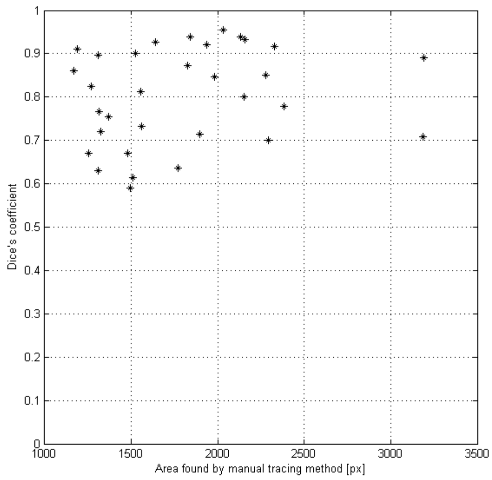


Figure 5.1: Area overlap using Dice's coefficient

The difference of the area found by the algorithm mapped to the manual tracing data is shown in figure 5.2 on page 26 as a Bland-Altman plot. If the difference is 0, there is no difference between the area found by the algorithm and the data of the manual tracing method.

The mean difference is 139.14, the absolute mean is 442.80 and the standard deviation is 601.74.

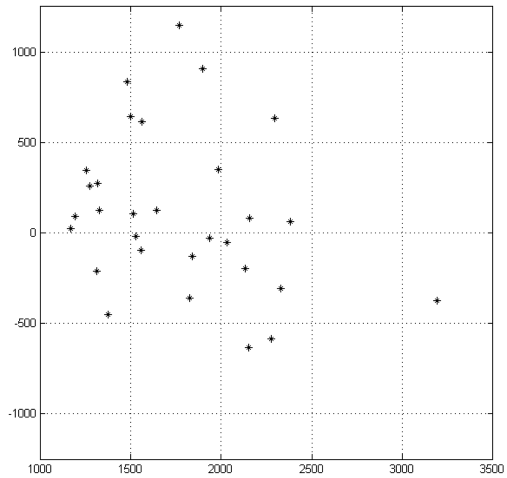


Figure 5.2: Bland-Altman plot of area

5.2 Perimeter

Figure 5.3 on page 27 also shows the reliability of the findings of the algorithm on the perimeter by mapping its difference. As with the graphs used above, the mean of the results from the five approximation of the median nerve is shown. The mean of the difference of the entire population is 1.47, while the absolute mean is 24.10 and the standard deviation is 33.77.

5.3 Circularity

The circularity has been evaluated using the same method as the perimeter, and its results are shown in 5.4 on page 27. The mean difference of the entire population is -0.08, the absolute mean difference is 0.18 and the standard deviation is 0.23.

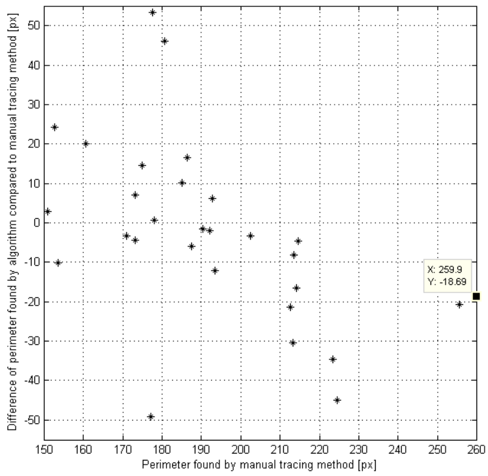


Figure 5.3: Bland-Altman plot of perimeter

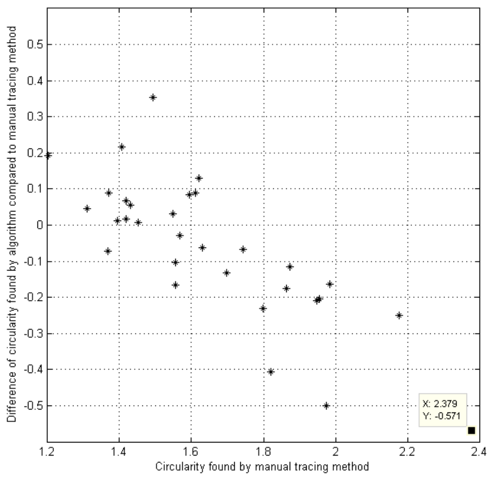


Figure 5.4: Bland-Altman plot of circularity

Chapter 6

Conclusion

The assignment was to develop an algorithm which could determine the area, perimeter and circularity of the median nerve in ultrasonographic imagery. Furthermore, its reliability had to be assessed compared to the manual tracing method.

The algorithm is able to determine all of these parameters, making use of a minimal cost analysis. A database has been developed in which its findings are data are stored.

Based on the results it can be concluded that the area found by the algorithm overlaps the manual tracing data by approximately 80%.

The results from the perimeter and the circularity show a trend where smaller values are overestimated while larger values are underestimated, which indicates a preference for a certain shape. This would suggest a number of recommendations in order for the algorithm to make a better estimation of the median nerve's shape. First of all, knowledge about the average size and shape could be included in the shape of the first iteration on which the scan lines are based upon. This would mean using an elliptic shape with the size of the average median nerve. By doing so the contour in the resampled image would be straighter than the contour currently found when using a circular shape to resample the image.

Another improvement would be to add an additional iteration which would use the contour of the previous one as the shape for the scan lines. This would also involve a variation in the parameters of the scan lines used, being the amount of scan lines, the number of samples taken per scan line and the space between these samples. In earlier iterations little is known about the contour to be found, calling for a rough evaluation of the area. This would mean a low amount of scan lines and samples per scan line, with much space between the samples. As the software moves through the iterations, the amount of scan lines and samples is augmented, while the space between the samples is reduced as to yield a more detailed image.

The way the cost of a position is currently being calculated is by looking at the direct neighbours of this position. This method also maps the noise in the image as costs, making it harder for the contour to be found. To make a better estimation of overall intensity gradients, a larger area around the position should be evaluated to calculate its costs.

Finally the way the direction of the scan lines is determined could be improved. This direction is defined as being perpendicular to the tangent of that position. The tangent is currently being calculated as a secant line through two points on either side of the position. In case of a shape with multiple curvatures, this can result in intersecting scan lines causing certain positions to be sampled twice. To overcome this, the mean coordinates of an area on both sides of the position should be calculated, on which the secant line should be calculated. This way the effect of small curvatures in the contour is minimized.

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